Technical Factors in Health App Adoption: Analyzing User Responses with Long Short-Term Memory Algorithm

1st Ariq Aqilah
Information System Department School of Industrial and System Engineering
Telkom University
Bandung, Indonesia
ariqaqilah@student.telkomuniversity.ac.id

2nd Rahmat Fauzi
Information System Department School of Industrial and System Engineering
Telkom University
Bandung, Indonesia
rahmatfauzi@telkomuniversity.ac.id

3rd Nur Ichsan Utama
Information System Department School of Industrial and System Engineering
Telkom University
Bandung, Indonesia
nichsan@telkomuniversity.ac.id

Abstract— **In Indonesia, health applications have emerged as a crucial component in improving healthcare access and quality. Despite the rapid growth of health applications, their adoption remains suboptimal due to challenges such as limited digital infrastructure, varying levels of IT literacy, and concerns about data privacy. This study seeks to address these challenges by categorizing the acceptability of health applications based on technical factors, utilizing the Long Short-Term Memory (LSTM) algorithm. The research is based on data collected through interviews with health application users in Bandung Regency with a primary focus on parents with children. The study compares two LSTM model scenarios: single-layer and double-layer. The findings reveal that perceived usefulness is the most significant factor influencing positive user responses, with system quality and facilitating conditions also playing crucial roles in enhancing user acceptance. The single-layer LSTM model achieved the highest accuracy of 84.5%, compared to 83.5% for the double-layer model. This study offers valuable strategies for developers to refine application features, ultimately contributing to improved healthcare accessibility and outcomes in Indonesia.**

Keywords— Health Applications, Adoption Factors, LSTM.

I. INTRODUCTION

Health remains a critical global concern. The United Nations has incorporated health as a key component of the Sustainable Development Goals (SDGs). In an effort to enhance the quality of healthcare services, the Indonesian government has invested considerable resources in health information systems [1]. In this regard, the development and implementation of health applications is a major initiative. Health applications have shown significant potential for improving the accessibility and quality of healthcare services, making them more accessible to the public [2]. The advancement of e-health in Indonesia will enhance healthcare access for over 260 million residents spread across 17,504 islands [3]. The use of information technology in healthcare in Indonesia may improve health outcomes, particularly for people in rural and remote areas [4]. Health applications in Indonesia have experienced rapid growth, particularly as government health facilities have transitioned online since the COVID-19 pandemic. This indicates a substantial shift in healthcare access, with health applications becoming the preferred option [5]. The healthcare system in Indonesia continues to enhance its service delivery and outcomes through an increase in the number of health services available [4].

Despite this growth, the adoption of health applications remains suboptimal, influenced by various factors related to user adoption and acceptance. User behavior is affected by design factors of the applications such as functionality, ease of use, security, and cost [6]. Furthermore, technical, individual, social/cultural, security, and health factors also play a crucial part in the acceptance of health applications. [7] Key issues reported include a lack of privacy protection, data security, infrastructure challenges, usability, and usefulness [8]. However, the growth of health app in Indonesia have shown promising outcomes in delivering healthcare services. Health is expected to address the challenge of distance in health service delivery, ensuring that healthcare reaches even the most remote areas across the country [9].

To tackle this issue, a study was conducted by interviewing users of health applications in Bandung Regency, with a primary focus on parents with children. This interview approach was selected because it provides deep insights into user experiences with health applications. This method is effective and suitable for collecting data[10]. The data collected was analyzed using Long Short-Term Memory to identify the technical factors influencing adoption. LSTM was selected due to its ability to overcome vanishing error problems. Moreover, LSTM includes extensions for self-resets and precise timing, enabling it to filter out irrelevant information from memory [11]. LSTM has demonstrated superior performance compared to CNN and traditional RNN, particularly in classification tasks. LSTM achieved the highest accuracy in classification, reaching 97.86% [12]. The primary motivation for this study is the urgent requirement to enhance healthcare accessibility throughout Indonesia by addressing technical challenges that impede the implementation of health applications. This research aims to contribute to the greater objective of improving public health outcomes by optimizing certain technical factors of health applications.

II. Related Works

Previous research has identified several factors that affect the adoption of health applications. [6] Emphasize the significance of demographic, technical, and social factors in determining user acceptance of health technology. They observe that motivation, demographic characteristics, information credibility, social influence, and regulatory frameworks shape user behavior. Similarly, [7] points out that technical, social/cultural, individual, health factors, and security play a crucial part in the acceptance of health app. [13] outlines seven primary criteria for adopting health applications, which include functionality, design, perceived user value, security and privacy, information, usability, and ethical considerations. Research [14] and [15] emphasize that multiple factors are linked to health applications adoption across organizational, individual, and contextual levels. Technological readiness, comprising affordability, ease of use, and motivational readiness, encompassing perceived usefulness, trust, and attitude, stand out as the most crucial elements among these.

Another study, [16] notes that expectations of effort, performance expectations, and facilitating conditions significantly impact the intention to use health applications. This demonstrates that health applications should provide robust support through efficient service and effective information processing. [17] Highlights that perceived severity, perceived ease of use, and vulnerability are crucial factors in the adoption of health application services among middle-aged and older adults. [18] Reveal that despite most reviews being positive, there are concerns regarding app costs and technical difficulties. [19] Demonstrate that the LSTM has an average precision, recall, and F1-score of 95% and a max accuracy of 95.38%. [20] Finds that the LSTM model surpasses the RNN algorithm in terms of network traffic prediction performance. Similarly, [21] asserts that text classification using LSTM and Bidirectional LSTM yields more accurate results, although with longer training times.

III. Methodology

A. CRISP-DM

CRISP-DM remains an essential framework for planning and overseeing data mining projects, continuing to be the widely accepted standard for creating data mining and knowledge discovery. [22]. CRISP-DM has six stages in its life cycle as depicted in Fig 1. The order of these phases is flexible, and it is common to move back and forth between them as needed [23].

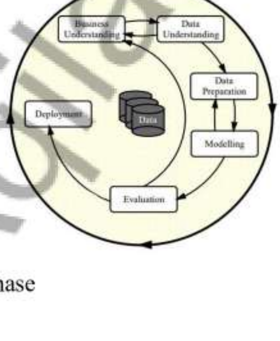

Fig. 1 CRISP-DM Phase

The Business Understanding phase focuses on understanding the goals and prerequisites of the project from a business standpoint. This understanding is transformed into a precise definition of the data mining problem and followed by the creation of an initial project plan to meet those goals [24]. The data understanding phase begins with the gathering of initial data and continues with activities aimed at familiarizing with the data, identifying data quality issues, uncovering preliminary insights, and detecting intriguing subsets to formulate hypotheses regarding concealed information.[23].

The data preparation phase involves creating the final dataset from the initial raw data for modeling. These tasks are performed multiple times and in no specific order, including selecting tables, records, and attributes, cleaning the data, creating new attributes, and transforming the data [24] During the modeling phase, various modeling techniques are selected and employed, with their parameters modified to get optimal results. For a given kind of data mining task, there are usually several approaches available, and some of them require particular data formats [24].

In the evaluation phase, a high-quality model has been built. Before final deployment, it is important to thoroughly evaluate the model and review the construction steps to ensure business objectives are met. The goal is to ensure that no important business issues have been overlooked. At the end of this phase, a decision regarding how to use the data mining findings needs to be made [24] Creating the model is usually not the final step of the project. The acquired knowledge must be organized and presented in a usable format for the customer. Depending on the needs, the deployment phase might range from producing a straightforward report to putting in place a sophisticated, repeatable data mining procedure [23].

B. Technical Factors

Based on the research conducted [6], [7], [12], [13], [14], [15], [16], [17] technical factors refer to the technological aspects that influence the adoption and implementation of health application services. The researchers have defined these technical factors into several aspects as follows:

- **Perceived Ease of Use** refers to an individual's perception that a specific technology can be used effortlessly and without significant effort [25].
- **Performance Expectancy** refers to the degree of belief that utilizing an information system will enhance an individual's ability to perform tasks more effectively [26].
- **Effort Expectancy** refers to the level of ease with which a system can be used, which can reduce the physical effort and time required by an individual to complete their tasks [26]
- **System Quality** refers to the technical attributes of a system that determine its ability to produce accurate and reliable information [27]. Poor system design can lead to limited access to the application [28].

- **Perceived Usefulness** refers to the level which a user believes that utilizing a system will improve their efficiency and help achieve desired goals [25].
- **Facilitating Conditions** refers to the belief in the availability of organizational support and technological infrastructure to facilitate the system [26].
- **Resistance to Change** describes the attitude of opposition that typically arises from technological changes [29].
- **Technological Incapability** refers to the condition where the necessary technology to operate or use an application is not widely available or sufficient [7].
- **Functionality** denotes the ability of a mobile health application to provide health services and information to users, with the quality of information being a key factor influencing the acceptance and use of the application [6].
- **Cost** is often the primary reason behind user reluctance to adopt mobile health applications, encompassing the costs of terminal devices, application purchases, and data traffic during application use [6].

IV. RESULTS AND EVALUATIONS

A. Business Understanding

The objective of this study is to assess the acceptance of health applications based on technical factors in Bandung Regency. Given the high demand for health applications in Indonesia, addressing barriers to their usage is crucial. This research will identify and categorize the technical elements that influence the acceptance of health applications. The effectiveness of the study will be measured by the accuracy of the LSTM model in classifying these technical factors. The classification model is built using the LSTM algorithm to produce accurate and relevant classifications. Model validation and evaluation will be conducted to ensure its effectiveness. This study is anticipated to make a substantial contribution to increase the adoption of health applications in Indonesia, with a focus on technical factors.

B. Data Understanding

This phase aims to identify potential issues in the data, with a primary focus on gathering information about the factors influencing the use of health applications. Data was collected through interviews with residents of Bandung Regency who use health applications. The interview questions were tailored to address specific technical factors. The interview results were recorded in audio format to ensure data accuracy and integrity, resulting in over 35,000 words and more than 1,500 rows of dataset.

C. Data Preparation

The next phase involves data preparation, which consists of several steps to clean, format, and prepare the raw data, as well as labeling it for analysis. These steps involve the removal of punctuation, double spaces, and irrelevant numbers, as well as case folding, stopword removal, stemming, tokenizing, and padding. This process utilizes tools and libraries such as Python, Keras, and Sastrawi, resulting in more than 1,000 unique words.

D. Modeling

The next phase involves training and validation. The LSTM algorithm is employed to build the model using the training data, with optimal architecture and parameter settings. The model is then compiled using appropriate loss functions, optimizers, and evaluation metrics. In the final stage, the model undergoes several iterations of training to minimize errors and enhance accuracy. The main configurations used include an 80:20 data ratio, 25 epochs, the Adam optimizer, batch sizes of 8, 16, and 32, and single-layers or double-layers LSTM.

E. Evaluation

The results were evaluated through two scenarios: a single-layer LSTM and a double-layer LSTM, each tested with batch sizes of 8, 16, and 32. The analysis of the results from these two scenarios provides deep insights into the impact of the number of layers and batch sizes on the LSTM model's effectiveness in processing data.

TABLE 1. Training and Validation Outcomes

Model	**Training Accuracy**	**Training Loss**	**Val Accuracy**	**Val Loss**
Single layer (8)	92%	0.0430	83.5%	0.0790
Single layer (16)	93%	0.0431	**84.5%**	0.0804
Single layer (32)	90%	0.0668	80%	0.0873
Double layer (8)	95%	0.0439	83%	0.0853
Double layer (16)	95%	0.0388	**83.5%**	0.0772
Double layer (32)	93%	0.0544	76%	0.1002

Table 1 demonstrates that the single-layer LSTM with a batch size of 16 achieved the highest validation accuracy at 84.5%, closely followed by the double-layer LSTM with the same batch size, which reached a validation accuracy of 83.5%. In terms of training accuracy, the double-layer LSTM models consistently outperformed the single-layer, with both the 8 and 16 batch sizes achieving 95% training accuracy. However, the validation results suggest that the single-layer model with a batch size of 16 strikes the best balance between training and validation performance. These results indicate that using a batch size of 16 in this dataset is the optimal choice to maximize the performance of the LSTM model for both single-layer and double-layer configurations.

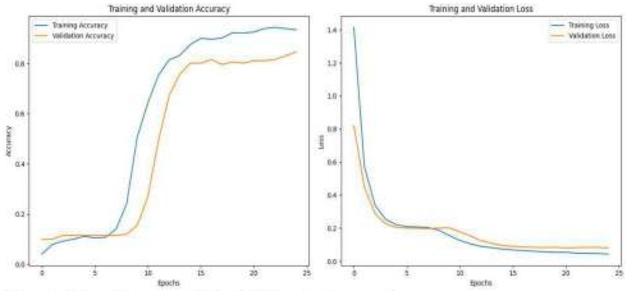

Fig. 2. Training and Validation Comparisons

Fig 2 shows the model's accuracy and loss from a single layer with a batch size of 16 over 25 epochs. Training accuracy increased significantly, reaching 0.9 by epoch 15, while validation accuracy reached 0.85 and continued to rise until epoch 25. Training loss dropped drastically until epoch 5 and stabilized around 0.1, with validation loss decreasing to nearly match the training loss. This graph shows consistent performance improvement, with increasing accuracy and decreasing loss, suggesting that the model does not suffer from significant overfitting and generalizes well.

TABLE 2. Classification Report of Each Aspects

Label	*Precision*	*Recall*	*F1-Score*	*Accuracy*
perceived ease of use	0.64	0.68	0.63	0.64
performance expectancy	0.85	0.70	0.70	0.75
effort expectancy	0.97	0.83	0.89	0.95
system quality	0.95	0.80	0.85	0.92
perceived usefulness	1.00	1.00	1.00	1.00
resistance to change	0.87	0.87	0.87	0.87
facilitating conditions	1.00	1.00	1.00	1.00
technological incapability	1.00	1.00	1.00	1.00
functionality	0.97	0.88	0.91	0.95
cost	0.95	0.95	0.95	0.95

According to Table 2, the model exhibits strong performance overall, with excellent precision, recall, F1-score, and accuracy for most labels. Notably, labels such as perceived usefulness, facilitating conditions, and technological incapability achieved perfect scores, demonstrating the model's high predictive accuracy in these areas. However, due to the limited data collected during interviews for these specific factors, labels like perceived ease of use and performance expectancy have lower accuracy scores. The smaller dataset for these labels made it more challenging for the model to perform effective training and validation, resulting in lower accuracy compared to other labels. Despite these areas for improvement, the model remains highly effective in predicting most labels with high accuracy.

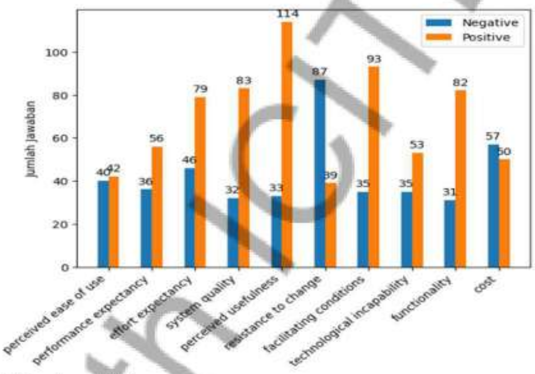

Fig. 3. Number of Responses

Fig. 3 illustrates that the label's perceived usefulness stands out with the highest number of positive responses, exceeding 114. This indicates that users overwhelmingly recognize the value and effectiveness of the health application in enhancing their experience or meeting their needs. The high volume of positive feedback suggests that users find the application significantly beneficial, which is a critical factor in their continued use and satisfaction.

Following closely, facilitating conditions also received a substantial number of positive responses, with over 90 users expressing favorable views. This reflects the importance users place on the external support and resources available to them, such as the ease of accessing the application and the availability of technical support. The strong positive response in this area highlights that when users feel adequately supported, they are more likely to have a positive overall experience with the health application.

In contrast, labels such as resistance to change and cost received more negative responses than positive ones, indicating that users are less satisfied with these aspects. This could indicate issues with the perceived value of the application in relation to its cost or a reluctance to adopt new technology. Despite these negative responses, the overall trend shows that most labels received more positive feedback, suggesting that users generally respond favorably to the health application, particularly in areas directly related to its usefulness and the support they receive.

V. CONCLUSSIONS

Research on the classification of health application acceptance using the LSTM algorithm has yielded several conclusions. Two testing scenarios were conducted with variations in LSTM layers and batch size. The single-layer LSTM model with a batch size of 16 obtained the maximum accuracy of 84.5%, while the double-layer model with the same batch size achieved 83.5%. Batch size 16 proved to be ideal for LSTM in this dataset, with accuracy and loss graphs showing significant performance improvements and excellent prediction results according to the classification report. Technical factors were found to be significant in the acceptance of health applications. Perceived usefulness was the most positively received factor, followed by system quality and facilitating conditions, which enhanced user trust and satisfaction. Affordable costs also increased accessibility and adoption of health applications.

For future research, it is recommended to conduct further interviews to obtain larger and more diverse data, thereby increasing the reliability and validity of the LSTM model as well as its adaptability to data variations. Additionally, exploring other algorithms such as Gated Recurrent Units (GRU) or Transformer is suggested. GRU has a simpler yet effective architecture for handling sequential data, while the Transformer algorithm with its attention mechanism has demonstrated outstanding performance in various NLP tasks.

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